The Gender Effects of COVID-19 on Equity Analysts*

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Abstract

We use the COVID-19 pandemic as a natural experiment to study the effects of childcare and household duties on sell-side analysts. The richness of this setting allows us to compare female and male analysts while requiring them to perform the same tasks. We find that female analysts' forecast accuracy declined more than male analysts, especially when schools were closed and among analysts who were more likely to have young children, inexperienced, were likely busier before the pandemic, and lived in southern states. Female analysts also reduced the timeliness of their forecasts and resorted to more heuristic forecasts. The stock market was aware of this and became less responsive to female analysts' forecasts. However, female analysts did not reduce their coverage or updating frequency relative to male analysts. We also find the above widening gender gap was temporary and became statistically insignificant by May/June 2020. Overall, our results show that the pandemic impacted female analysts more than males through the quality of their forecasts but not the quantity.

Keywords: COVID-19; financial analysts; gender gap; decision heuristics
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1. Introduction

A persistent gender gap exists in business, especially at the top echelons, with women underrepresented. For example, women represented less than 10% of CEOs, CFOs, and board directors among listed firms (Wolfers, 2006; Adams and Ferreira, 2009; Huang and Kisgen, 2013), mutual fund managers (Atkinson, Baird, and Frye, 2003; Niessen-Ruenzi and Ruenzi, 2019), venture capital general partners (Gompers et al., 2019; Ewens and Townsend, 2020), and sell-side security analysts (Kumar, 2010; Fang and Huang, 2017). Studies have also demonstrated that women face higher hurdles with being successful. For example, female fund managers receive significantly lower inflows (Atkinson, Baird, and Frye, 2003; Niessen-Ruenzi and Ruenzi, 2019). Female-led startups experience significantly more difficulty garnering interest and raising capital (Ewens and Townsend, 2020; Hebert, 2020). The financial advisor industry is more forgiving of misconduct by men relative to women (Egan, Matvos, and Seru, 2021). Female analysts benefit less from connections in both job performance and the subjective evaluation by others (Fang and Huang, 2017), and get lower media coverage (Kumar, 2010). Benson, Li, and Shue (2021) document that women are significantly less likely to be promoted despite receiving higher performance evaluations.

The spread of the COVID-19 pandemic and subsequent countermeasures such as school closures and social distancing are likely to exacerbate these gaps. School and daycare center closures increased childcare needs dramatically. Due to social distancing requirements, many parents had little choice other than to take care of their children themselves, at least at the beginning of the pandemic. Given that mothers took responsibility for a much larger share of childcare and household duties than fathers (Alon et al., 2020; Deryungina, Shurchkov, and Stearns, 2021), we

expect women to be more affected than men during the pandemic. Hence, the pandemic provides a natural experiment to study the effects of childcare and household duties on the gender gap.

Challenges exist in estimating the gender effect of the pandemic. In many sectors, men and women performed different tasks that were affected differently. The COVID-19 pandemic caused not only a public health crisis but also an economic one. It had heterogeneous impacts on different sectors and different types of jobs. For example, the pandemic had a larger impact on the sectors with more woman employees, contributing to a larger increase in the unemployment rate of women than men (Adams-Prassl et al., 2020; Alon et al., 2020; Cajner et al., 2020; Mongey et al., 2021). Even within the same sector, men and women might perform different tasks that were affected differently. Distinguishing the gender effect from other possible effects (such as sector or task effects) is important from a policy perspective. If sector composition is driving the gender gap widening, relief policy should target sectors instead of targeting gender.

This paper studies how the pandemic affected female and male sell-side equity analysts differently using a difference-in-differences approach. The richness of the setting allows us to compare female and male analysts while requiring them to perform the same tasks: forecasting the same firms' earnings of the same fiscal quarter. Hence, our estimate allows us to have a clean gender effect estimate that is free of other confounding factors.

The analyst setting is unique in several other dimensions. First, in contrast to many other sectors, the analyst sector features superior skills of female analysts. Female analysts issue more accurate forecasts, and their revisions have a stronger market impact. Kumar (2010) attributes this pattern to gender-based selected entry: female analysts with superior forecasting abilities enter the profession due to a perception of discrimination in the analyst labor market. Second, the analyst job is time-consuming and requires analysts to provide timely updates on covered firms when

receiving new information. Such a job requirement allows researchers to capture the potential impacts of an increased parenting burden on their job performance. Third, individual analysts' performance can be objectively measured. Individual analysts forecast the earnings of the firms they cover, and we can compare their forecasts with the realized earnings, giving us a direct and objective measure of individual productivity. Individual analysts issue their forecasts relatively frequently, giving us a timely measure of their accuracy. In our empirical analysis, we focus on analysts' forecasts of firms' quarterly earnings. Lastly, analysts' forecast announcements are dated, allowing us to study the dynamics of analyst forecast behaviors before and during the pandemic. This setting also allows us to measure the *quantity* (i.e., the number of firms covered and updating frequency) and the *quality* (i.e., accuracy and timeliness) of analyst forecasts. In contrast, the literature on the gender effect of COVID-19 has focused on studying quantity.

Our analysis reveals that female analysts' forecast error significantly increased relative to that of male analysts due to the pandemic, but changes in the number of firms covered and updating frequency are not related to analyst gender. The effect is economically sizable. The relative increase in forecast error is 14.5% of the unconditional average. Consistent with the conjecture that the parenting burden disproportionately fell on the shoulders of women, we find that these results are stronger when schools were closed and among analysts who were more likely to have young children. The results are stronger among analysts living in southern states where gender role attitudes are, in general, more traditional (Rice and Coates, 1995; Ke, 2021). These results are also stronger among analysts who were less experienced and busier (i.e., covered more stocks) before the pandemic, consistent with the view that the pandemic was a time allocation shock that affected female analysts more strongly.

Consistent with Hirshleifer et al. (2019) that judgments and decisions made under greater pressure, distraction, or fatigue (i.e., a decline in decision quality after an extensive session of decision making) tend to be made more heuristically, we find that, as a result of the pandemic, relative to male analysts, female analysts herded more closely with the consensus forecast, had a higher likelihood of reissuing their previous outstanding forecast, and had a higher likelihood of issuing a rounded forecast. Female analysts were also less likely to provide timely forecasts right after firms' earnings announcements.

Stock market participants were aware of the asymmetric impact of the pandemic on male and female analysts' forecast quality. Consistent with Kumar (2010), we find that the forecast revisions made by female analysts had a stronger market response before the pandemic. Such a pattern reversed during the pandemic, although the during-pandemic difference was not statistically significant.

This widening gender gap decayed quickly and disappeared by May/June 2020. In March 2020, at the outset of the pandemic, the relative increase in female analysts' forecast error was more than 20% of the unconditional average. In April and May 2020, the relative increase in female analysts' forecast error shrank to around 10% of the unconditional average. From June to August 2020, it further shrank to less than 5% of the unconditional average and became statistically insignificant. Our finding that the gender gap widened the largest at the pandemic outbreak and started to shrink around May and June is consistent with Alon et al. (2021), who study the gender gap in unemployment. However, Alon et al. (2021) report that, in the general population, the widening gender gap persisted much longer. The difference suggests that the analysts were affected less severely relative to the general population.

Overall, the evidence is consistent with the parenting burden disproportionately falling on the shoulders of women. One alternative mechanism is that women became more pessimistic during an economic downturn, and female analysts' forecasts became more pessimistic and less accurate.[1] Examining a direct measure of forecast optimism, we find no evidence that forecasts made by female analysts became more pessimistic relative to male analysts during the pandemic. Besides, we use the 2007-2009 global financial crisis as a placebo and do not find any evidence of a widening gender gap during that economic downturn. Another possibility is that the pandemic increased the competitiveness of the analyst job with a rising unemployment rate and the challenging job market. Studies show that men have a stronger preference for and a better ability to respond to the increased competitiveness (Gneezy, Niederle, and Rustichini, 2003; Niederle and Vesterlund, 2007; Reuben, Sapienza, and Zingales, 2015). However, this alternative story is inconsistent with the placebo results from the global financial crisis, which hit the financial industry more severely than the COVID-19 pandemic.

Our main contribution is providing causal evidence supporting the existence of the motherhood penalty among finance professionals. In sociology and other non-finance fields, there is a well-established strand of literature on the motherhood penalty: having children hurts women in pay, perceived competence, and benefit (Budig and England, 2001; Anderseon, Binder, and Krause, 2002; Correll, Benard, and Paik, 2007). Although the role of gender in finance has received extensive attention (Barber and Odean, 2001; Goldsmith-Pinkham and Shue, 2021; and studied cited at the beginning of this paper), the motherhood penalty is relatively underexploited.

[1] One possible reason is that women may have more woman friends who were more negatively affected by the pandemic. Similar to the experience effect (Malmendier and Nagel, 2011; D'Acunto, Malmendier, and Weber, 2020), this might have led women to have more pessimistic expectations about the pandemic than men.

Our finding is consistent with several recent studies that document a widening gender gap during the pandemic. Cajner et al. (2020) document that employment declines caused by the pandemic were about four percentage points larger for women than for men. Coibion, Gorodnichenko, and Weber (2020) document that the pandemic caused more women than men to quit the labor force. Alon et al. (2020) and Alon et al. (2021) argue that the pandemic had a larger impact on sectors with high female employment shares, explaining part of the unequal employment declines. Most other studies on the gender effects of the pandemic focus on academics from various fields (Amano-Patino et al., 2020; Andersen et al., 2020; Barber et al., 2021; Cui, Ding, and Zhu, 2021; Deryungina, Shurchkov, and Stearns, 2021; King and Frederickson, 2020; Kruger, Maturana, and Nickerson, 2020; Myers et al., 2020; Vincent-Lamarre, Sugimoto, and Lariviere, 2020). These studies measure academic productivity either by survey or by counting the number of working papers or journal submissions.

We highlight several distinctions of our study. First, the existing studies either examine the employment rate or the *quantity* of academic research output. In comparison, our findings emphasize the *quality* dimension of productivity. Interestingly, we find no gender difference in terms of the quantity of research output of analysts. These findings suggest the importance of considering both quantity and quality in measuring productivity. Second, another concern of the above studies is that the pandemic might have heterogeneous impacts along other dimensions that correlated with gender, confounding the estimation of the gender effect. For example, men and women might have different subfield expertise. The pandemic created new research opportunities, and these new opportunities benefited female and male academics unequally.[2]

[2] King and Frederickson (2020) and Cui, Ding, and Zhu (2021) document a surge in the number of preprints newly uploaded to several preprint depositories such as bioRxiv (a preprint server mainly for biological science), arXiv (a preprint server mainly for physics, math, computer science, and statistics), and Social Science Research Network

We also contribute to the literature studying how pressure, distraction, and fatigue affect decision-making (e.g., Hirshleifer, Lim, and Teoh, 2009; Hirshleifer et al., 2019; Driskill, Kirk, and Tucker, 2020). Most related to us is Hirshleifer et al. (2019), who document that analyst forecast accuracy declines over the course of a day as the number of forecasts the analyst has already issued increases. Hirshleifer et al. (2019) point out that one alternative interpretation for their finding is that analysts choose to structure their workday by first working on forecasts for which they have high-quality information relative to the consensus. Although not directly on fatigue, our study provides causal evidence that distraction hurts decision quality.

Our study is one of the first to study how the pandemic affected analysts. Equity analysts are important information intermediaries, and their proper functioning is critical to the functioning of capital markets. Landier and Thesmar (2020) and Hong et al. (2021) use analyst forecasts to study the market's earnings expectations during the pandemic. Dechow et al. (2021) study the relationship between implied equity duration and analyst forecast revisions in response to the pandemic. However, they do not study the gender effect.

The effects of COVID-19 that we document have implications that extend beyond financial analysts and the specific setting of the pandemic. Although different sectors may have different production functions, labor time is almost always one of the most important inputs. Our findings suggest that the increased childcare and household duties disproportionately fell on the shoulders of women, even among financial professionals and in a sector where females are known to have

(SSRN), consistent with the pandemic creating new research opportunities. Evidence shows that female researchers are underrepresented in the new and flourishing area of COVID-19 research for many fields (Vincent-Lamarre, Sugimoto, and Lariviere, 2020), such as economics (Amano-Patino et al., 2020) and medical research (Andersen et al., 2020). Chari and Goldsmith-Pinkham (2017) report a large dispersion of the fraction of female authors across NBER Summer Institute programs.

superior skills. Our findings echo policy responses that account for the disparate effects of a common adverse shock (Oleschuk, 2020; Barber et al., 2021).

2. Data

Data on analysts' earnings per share (EPS) forecasts are collected from the Institutional Brokers' Estimate System (I/B/E/S) Detail History file, covering the period from January 2019 to August 2020. We focus on quarterly EPS forecasts as we want to study analysts' timely forecast activities. CRSP had not updated the daily stock return data to 2020 yet when we worked on this project. We obtain daily stock prices from Compustat North America and follow Bessembinder et al. (2020) to compute daily returns for individual stocks.

Our sample starts with the 2,351 analysts who provided earnings forecasts in 2019. First, we identify an analyst's last name, first initial, and brokerage affiliation using the I/B/E/S Detail Recommendation file. The majority of analysts participated in firms' earnings conference calls. From the earnings conference call transcripts provided by FACTSET Events & Transcripts, we obtain participants' full names and affiliations and match them with the I/B/E/S analysts.[3] An analyst's full name is identified if the last name, first initial, and brokerage affiliation match the equivalent information from the conference call transcripts.[4] Through this procedure, we identify 2,097 analysts' full names. Second, we hand collect analysts' gender, location, and the college

[3] An earnings conference call typically has two parts: managerial presentation and questions-and-answers between analysts and firm managers. We use text parsing tools to go through each transcript and extract the full names and affiliations of all conference call participants. Due to career concerns, sell-side analysts have a strong incentive to participate in earnings conference calls hosted by their covered firms, as information conveyed during such calls provide important inputs to their forecasts and recommendations (Mayew, Sharp, and Venkatachalam, 2013; Jung, Wong, and Zhang, 2015).

[4] Very often, brokerage names are spelled differently. We conduct manual matching of brokerage names for analysts whose last names and first initials match across I/B/E/S and the earnings conference call transcript data.

graduation year from LinkedIn. If an analyst does not have a LinkedIn profile, we conduct a Google search. In a small number of cases, we can locate these analysts from other professional web pages. If LinkedIn or other web searches do not return sufficient information, we infer analysts' gender based on their first names. This step results in the number of analysts with gender information to 1,968. Analysts' age is generally not directly available, and we calculate an analyst's age by assuming that analysts graduated from college at the age of 22.

Our primary dependent variable of interest is analyst forecast accuracy, inversely proxied by analysts' percentage absolute forecast error (*Forecast Error*). *Forecast Error* for analyst i on stock j's EPS of quarter q issued at time t is equal to the absolute value of actual company EPS minus the EPS forecast of analyst i for firm j at time t, divided by the stock's price twelve months prior to the quarterly earnings announcement date and multiplied by 100.

$$Forecast\ Error_{i,j,q,t} = 100 * \frac{\left|Actual\ EPS_{j,q} - Forecasted\ EPS_{i,j,q,t}\right|}{Price_{j,q-4}}$$

Given time constraints, analysts may reduce the quantity of their forecasts to maintain their forecast quality (i.e., accuracy). We use two measures to capture the quantity dimension of analyst forecasts. The first measure is *Firms Covered*, which we define as the number of unique firms an analyst covers. The second measure is *Updating Frequency*, which we define as the number of forecasts an analyst issues for every firm they cover at the monthly level.

We also calculate several other variables to capture analysts' forecast activities. Following Clement and Tse (2005), we define $Herding_{i,j,q,t}$ as a dummy variable that takes the value of one if analysts i's forecast of company j's EPS of quarter q is between the consensus forecast at time t and the analyst's previous forecast, and zero otherwise. Following Dechow and You (2012), we define $Rounding_{i,j,q,t}$ as a dummy variable that takes the value of one if a forecast ends with zero

or five in the penny digit, and zero otherwise. Following Hirshleifer et al. (2019), we define $Reissue_{i,j,q,t}$ as a dummy variable that takes the value of one if a forecast is reissued, and zero otherwise. Hirshleifer et al. (2019) argue that analysts tend to resort to more heuristic decisions under greater pressure, distraction, or fatigue by herding more closely with the consensus forecast, reissuing their previous outstanding forecasts, and issuing a rounded forecast. Following Dehaan, Madsen, and Piotroski (2017), we define $Timeliness_{i,j,q,t}$ as a dummy variable that takes the value of one if analyst *i* issues an EPS forecast within days [0, +2] of firm *j*'s earnings announcement at quarter *q*, and zero otherwise.

Table 1 reports the summary statistics of the main variables in our analysis for female and male analysts separately. Panel A is based on the entire sample. In Panel B, we calculate analyst forecast characteristics using the pre-pandemic data. We winsorize the continuous variables at the 1% and the 99% levels to mitigate the impact of outliers. There were 1,968 unique analysts in our sample, 224 of which were female. The mean age of male and female analysts was 37 and 34, respectively. In total, female analysts made 41,409 forecasts, and male analysts made 343,428 forecasts. The fraction of female analysts in our sample is similar to that reported by Fang and Huang (2017). These analyses were affiliated with 184 unique brokerage firms.

Female and male analysts showed remarkably similar forecast characteristics before the pandemic outbreak. Female analysts had a slightly lower *Forecast Error* than male analysts. The mean *Forecast Error* was 1.118 (e.g., 33.5 cents for a $30 stock) and 1.145 (e.g., 34.4 cents for a $30 stock) for female and male analysts, respectively. This finding is consistent with Kumar (2010), who finds that female analysts issue more accurate forecasts. Both female and male analysts covered a similar number of firms (12.197 for females and 12.871 for males). Every month, female analysts issued 1.124 forecasts for every firm they covered, and male analysts

issued 1.116 forecasts. Female analysts issued a higher fraction of herded forecasts (36.1% for females vs. 34.0% for males). Female analysts issued a lower fraction of rounded forecasts (17.2% for females and vs. 18.9% for males) and had a lower likelihood of reissuing a previous forecast (47.0% for females vs. 51.1% for males). Male analysts made more timely forecasts (49.1% for females and 50.2% for males). However, all the differences are economically small. *Forecast Age* is the natural logarithm of the number of calendar days from the forecast to the earnings announcement date (Clement, 1999). Female and male analysts showed very little difference in *Forecast Age*. On average, forecasts issued by both the female and male analysts were announced about 141 days (i.e., exp(4.95)) before the earnings announcements.

3. Empirical Results

3.1 Forecast accuracy

3.1.1 Baseline results

Our main prediction, based on the existing literature and the assumption that mothers increased their childcare time more than fathers did, is that COVID-19 affected female analysts more than male analysts, and female analysts would issue less accurate EPS forecasts after the pandemic outbreak than male analysts. To conduct the test, we estimate the following regression model:

$$Forecast\ Error_{i,j,q,t} = \beta_1 Female_i * Post_t + \beta_2 X_{i,j,q,t} + \gamma_{j,q} + \delta_{i,j} + \theta_t + \varepsilon_{i,j,q,t}$$

where i indicates analysts, j indicates firms, q indicates the fiscal quarter to which the analyst's forecast applies, and *t* indicates the day when the analyst issues the forecast. $Female_i$ is a dummy

variable that takes the value of one if analyst i is female, and zero otherwise. $Post_t$ is a dummy variable that takes the value of one if a forecast is issued after the COVID-19 outbreak, and zero otherwise. Specifically, we define the post-period to be from March 1, 2020, onward. We choose March 1, 2020, because the surge of diagnosed COVID-19 cases started from early March 2020, and the majority of the states issued mandatory school closing orders in March 2020. Our results are similar if we use March 15, 2020, as the cutoff. $X_{i,j,q,t}$ is a set of control variables. The primary variable of interest is $Female_i * Post_t$. If female analysts were affected more by COVID-19, we expect $\beta_1 > 0$.

In all of the specifications, we include the *Firm* × *Fiscal Quarter* fixed effects ($\gamma_{j,q}$). With the *Firm* × *Fiscal Quarter* fixed effects, we essentially compare different analysts' forecast accuracy by requiring them to perform the same tasks: forecasting the same firms' earnings of the same fiscal quarter.[5] Depending on the specification, besides the *Firm* × *Fiscal Quarter* fixed effects, we include several other groups of fixed effects. In the most stringent specification, we have *Analyst* × *Firm* fixed effects ($\delta_{i,j}$) and year-month fixed effects (θ_t). Note that $Female_i$ is absorbed by the *Analyst* × *Firm* fixed effects, and $Post_t$ is absorbed by the year-month fixed effects. The *Analyst* × *Firm* fixed effects also absorb the *Analyst* fixed effects.

Given the granularity of our panel data, we can estimate all of these high-dimensional fixed effects simultaneously. With all of these fixed effects included, our estimated effect comes from comparing the change in forecast accuracy by female analysts from pre- to during-COVID-19

[5] There is another widely used method to control for the firm- or time-specific factors that affect forecast accuracy (Jacob, Lys, and Neale, 1999; Clement, 1999; Hong, Kubik, and Solomon, 2000; Cowen, Groysberg, and Healy, 2006). In this method, researchers adjust the accuracy of an analyst's EPS forecasts for a particular firm at a given time by subtracting the mean level of accuracy for all analysts who make forecasts for the same firm and time period within a comparable forecast horizon. In light of Gormley and Matsa (2014), we prefer the fixed-effect method.

periods, relative to any potential change in forecast accuracy of male analysts covering the same stock over the same period. Given this stringent empirical specification, we need to control only factors that vary at the analyst-firm-time level. We, therefore, only include *Forecast Age*. Our results hold with the standard set of controls (see Table A1 in the Internet Appendix). We cluster our standard errors by analysts. Our results are similar if we double-cluster standard errors by analysts and forecast months.

Table 2 reports the regression results. In column (1), we add the *Firm* × *Fiscal Quarter* and the *Analyst* fixed effects. In column (2), we add the *Firm* × *Fiscal Quarter*, the *Analyst* × *Firm*, and the year-month fixed effects. In column (3), we further add *Forecast Age*. The coefficient of *Forecast Age* is strongly positive, consistent with the prior literature that forecasts issued closer to earnings announcements are more accurate (Clement, 1999). The coefficient of $Female * Post$ is around 0.16 in all three specifications, suggesting that our results are not sensitive to changes in empirical specifications. The coefficient is statistically significant at the 1% level in all three specifications. These results indicate that, relative to male analysts, female analysts' earnings forecasts became less accurate after the pandemic outbreak. This finding is consistent with our prediction.

The economic magnitude of the relative decrease in forecast accuracy for female analysts is sizable. As shown in Table 1, the mean of *Forecast Error* in our sample before the pandemic is about 1.1. Hence, the relative decrease in forecast accuracy for female analysts, as estimated in Table 2, is 14.5% of the unconditional mean, an economically meaningful effect (e.g., 38.4 cents rather than 33.5 cents on a $30 stock).

We report several robustness tests in Table A1 of the Internet Appendix. In column (1), we report the results when we double-cluster standard errors by analysts and forecast months. In

column (2), we winsorize *Forecast Error* at the 2% and 98% levels. In column (3), we focus on the period from September 2019 to August 2020. Under this choice, the pre- and the post-periods have the same length. In column (4), we use March 2019 to August 2019 as the pre-period to control for the possible seasonality effect in analyst forecasts. In column (5), we control for a group of analyst characteristics. Most of these analyst characteristics are slow-moving. Thus, it is not surprising that most variables are statistically insignificant, as we have already included the *Analyst* × *Firm* fixed effects. Overall, our results are similar across these different specifications.

3.1.2 Dynamic effects

To test the dynamic treatment effect, we separate the whole sample period into seven subperiods: each of the five months around March 2020, December 2019 or before, and June 2020 or after. Then we interact these subperiod dummy variables with the *Female* dummy and run similar panel regressions as in Table 2 while including the year-month fixed effects.

Table 3 reports the results. In column (1), we include the *Firm* × *Fiscal Quarter* and the year-month fixed effects. In this specification, we can estimate the gender difference for each subperiod. The results show that female analysts' forecast error was smaller in the pre-period than male analysts'. The statistical significance of the estimation of the pre-period gender difference is weak, perhaps because our sample is much smaller than that of Kumar (2010). In the first three months after the pandemic outbreak, female analysts' forecast error became significantly bigger than male analysts'. By June 2020, the difference was still positive but became insignificant.[6]

[6] We group June-August 2020 into one group. The results are qualitively similar if we conduct the analysis month by month.

In column (2), we further include the *Analyst* × *Firm* fixed effects. In this specification, we cannot estimate the gender difference for each subperiod anymore. We use the month right before the pandemic outbreak (i.e., February 2020) as the base case and evaluate the gender differences for each of the other subperiods relative to that of February 2020. We find similar results that female analysts' forecast error relative to male analysts increased the most in March 2020, gradually shrank in subsequent months, and by May 2020, the difference became insignificant.

Figure 1 displays the results graphically. We plot the estimated coefficients (and 95% confidence intervals) of the interaction between subperiod dummy variables with the Female dummy and control for the *Firm* × *Fiscal Quarter*, *Analyst* × *Firm*, and year-month fixed effects and *Forecast Age*. The figure shows that female analysts' forecast errors (relative to male analysts) increased the most in March and April 2020, and the difference became insignificant afterward.

Taken together, Table 3 and Figure 1 report two important findings. First, the pandemic affected female analysts more than male analysts. The effect started right after the pandemic outbreak and became weaker afterward. Second, there were no pre-event trends in gender difference. The latter suggests that the parallel trends assumption underlying our difference-in-differences estimation is likely valid.

3.2 Potential economic mechanisms and supporting evidence

In this subsection, we conduct empirical tests to examine the underlying economic mechanisms of the above-documented widening of the analyst gender gap. Our main conjecture is that the parenting burden disproportionately fell on the shoulders of women. Such an asymmetric increase

in parenting burden caused a more significant time allocation shock to female analysts than male analysts.

In subsection 3.2.1, we examine the quantity of forecasts to have a complete understanding of analyst productivity. In subsection 3.2.2, we examine the school closure effect. In subsection 3.2.3, we examine the cross-analyst heterogeneity to shed more direct light on the conjectured mechanism. In subsection 3.2.4, we investigate several other measures of analyst forecast behaviors. In subsection 3.2.5, we examine one alternative mechanism. In the last subsection, we conduct a placebo test based on the 2007-2009 global financial crisis.

3.2.1 Quantity: firms covered and updating frequency

If analysts' time became more constrained during the pandemic, analysts might face a tradeoff between forecast quality (i.e., accuracy) and forecast quantity (i.e., firms covered and updating frequency). Table 4 examines whether the pandemic affected female and male analysts differently regarding updating frequency (Panel A) and firms covered (Panel B).

We measure *Updating Frequency* at the analyst-firm-month level. Specifically, we define updating frequency as the number of forecasts issued by analyst *i* in month *t* for firm *j*. To estimate the effect of the pandemic, we use the same model as in Table 2 by replacing the dependent variable with updating frequency. In this test, we do not include *Forecast Age*, as this variable is not well defined for *Updating Frequency*. In both specifications, the coefficient of $Female * Post$ is insignificant. The magnitude is also tiny. The coefficient is between 0.0028 and 0.0035. The average updating frequency is about 1.12 for both female and male analysts. Therefore, 0.0028 or 0.0035 is negligible.

We measure *Firms Covered* as the number of unique firms on which an analyst issued at least one forecast. The analysis is at the analyst-period level. For each analyst, we have two observations: one for the pre-period and one for the post-period. In the regressions, we either use *Firms Covered* or the natural logarithm of *Firms Covered* as our dependent variable. Our results indicate that, in all the specifications, the coefficient of $Female * Post$ is never significant, suggesting that the pandemic did not have an asymmetric impact on female and male analysts in terms of the number of firms followed.

3.2.2 The school closure effect

We obtain our school closure and reopening dates at the state level from Ballotpedia, which tracks state-level orders related to school openings and closures.[7] Most states leave reopening decisions to local health officials, schools, school boards, and districts. We define reopening date as to when schools in a state were officially allowed to reopen to in-person instruction as long as the school district meets certain health-related criteria. As an example, we define August 17, 2020, as the reopening date for Arizona, which according to Ballotpedia, is the date when schools in Arizona were officially allowed to reopen to in-person instruction if they meet metrics the state Department of Health released in the week of August 3. By the end of August 2020, 18 states had allowed school reopening. The remaining states reopened schools after August 2020.

We create a dummy variable, *Closure*, that takes the value of one if a forecast was issued when the schools were closed in the state the analyst resided, and zero otherwise. School reopening does not mean that school activities would be back to the pre-pandemic normal. With the health concern,

[7] https://ballotpedia.org/School_responses_to_the_coronavirus_(COVID-19)_pandemic_during_the_2020-2021_academic_year.

many parents chose not to send their children back to school. Many schools decided not to open even after they were allowed to. Many schools did not resume their after-school programs. Schools still needed to follow social distancing. In many cases, the maximum permitted enrollment was lower than the pre-pandemic level. As a result, many students could not return to school even if their parents wanted to.

We expect that the female-male analyst gap was bigger when schools were closed than when schools were allowed to open. We also expect that even when schools were allowed to reopen, the female-male analyst gap was still bigger than the pre-pandemic level.

Table 5 reports the results on the school closure effect. We replace the $Female * Post$ variable in the baseline model with two variables, $Female * Post * (Closure = 1)$ and $Female * Post * (Closure = 0)$. Consistent with our conjecture, Table 5 shows that the coefficient of $Female * Post * (Closure = 1)$ is larger than the coefficient of $Female * Post * (Closure = 0)$. The coefficient of $Female * Post * (Closure = 0)$ is significantly positive, suggesting that even when schools were not officially closed, female analysts were also affected more, consistent with the above discussions.

The results on school closures are consistent with our conjecture that the parenting burden disproportionately fell on the shoulders of women, and such an asymmetric change drove the relative decrease in female analysts' forecast accuracy.

3.2.3 Cross-analyst heterogeneity

To provide direct evidence to the parenting burden explanation, ideally, we would like to have information about analysts' family structure, such as whether the analyst was married and how

many children he/she needed to take care of. Such information is difficult to access. The results based on school closure are consistent with this interpretation. In this subsection, we further substantiate this interpretation by exploring the cross-sectional heterogeneity in analyst characteristics. Specifically, we evaluate analyst age, firms covered, and experience. We also examine whether an analyst lived in a southern state where gender role attitudes are, in general, more traditional (Rice and Coates, 1995; Ke, 2021). We use the Census Bureau's designation to define southern states.

If parenting burden was the main reason for the widening gender gap, we expect that the gender gap increased the most among middle-aged analysts because they were most likely to have young children. We also expect that the pandemic increased the gender gap more for busier analysts and relatively inexperienced analysts because their time was more likely to be constrained. Similarly, we expect the pandemic increased the gender gap more for analysts living in southern states.

Panel A of Table 6 reports the results on age. We split all the analysts into four groups based on analyst's age: less than 30, between 30 and 40, between 40 and 50, and older than 50. We then run the same panel regressions as in our baseline regressions (Table 2) on each subsample. Consistent with our conjecture, the coefficient of $Female * Post$ is largest and most significant when analysts' age is between 30 and 40. Relative to the analysts between 30 and 40 years old, the younger analysts were less likely to have children, and the childcare duty was perhaps less demanding for more senior analysts whose children are either older or have grown up.

In Panel B, we split our sample into two groups based on the number of firms covered, analyst total experience, or analyst location. *Firms Covered* is defined as the number of firms covered by the analyst in a year. *Total Experience* is defined as the number of years since the analyst issued the first forecast for any firm. We calculate both *Firms Covered* and *Total Experience* using data

before the pandemic. We expect that analysts who needed to cover a larger number of firms were busier. As the pandemic serves as a time allocation shock, we expect the gender gap became wider among busier analysts. We also expect the gender gap became wider among inexperienced analysts and analysts living in southern states.

The results in Panel B are consistent with these conjectures. The coefficient of $Female * Post$ is larger and more significant for analysts with a larger number of firms to follow, for inexperienced analysts, and for analysts living in southern states.

Taken together, the cross-analyst heterogeneity tests and the school closure results are consistent with our conjecture that the parenting burden disproportionately fell on the shoulders of women and caused the widening gender gap in forecast quality.

3.2.4 Forecast heuristics and timeliness

We now examine whether female analysts who were likely overburdened by childcare and other household duties resorted more to heuristics when making forecasts and issued less timely forecasts. Following Hirshleifer et al. (2019), we consider three measures of decision heuristics. We expect that, relative to male analysts, female analysts were more likely to issue a herding forecast, more likely to reissue his/her previous forecast, and more likely to issue a rounded forecast during the pandemic than before the pandemic.

To provide further evidence on female analysts being overburdened during the pandemic, we can look at situations when the job task is more demanding. One such situation is earnings announcements, as analysts are expected to update their forecasts within a short window following earnings announcements (as can be seen from the high unconditional probability of updating

immediately after earnings announcements in Table 1). We expect that relative to male analysts, female analysts were less likely to update their forecasts immediately after earnings announcements during the pandemic than before the pandemic.

We use a similar difference-in-differences specification as our baseline regression to analyze *Herding*, *Reissue*, *Rounding*, and *Timeliness*. All these four dependent variables are dummy variables. Hence, we use a linear probability model to incorporate our fixed effects to avoid the incidental parameters problem of nonlinear models such as logic and probit (Neyman and Scott, 1948; Lancaster, 2000).

Table 7 reports all the results. For *Herding*, *Reissue*, and *Rounding*, we run three specifications as in our baseline results. For all the three variables, the coefficients of $Female * Post$ are not sensitive to the model specifications. Hence, we focus on the most stringent specification with all the fixed effects and the control of *Forecast Age*. The coefficients of $Female * Post$ are positive in Panels A-C. These results show that, relative to male analysts, female analysts were more likely to issue a herding forecast, reissue their previous forecast, and issue a rounded forecast during the pandemic than before the pandemic. For *Timeliness*, we do not control for *Forecast Age* because it mechanically correlates with *Timeliness*. Female analysts' forecast timeliness exhibited a relative decrease, as indicated by a negative coefficient of $Female * Post$ in Panel D.

The economic magnitude of these coefficients is non-trivial. The results indicate that, relative to male analysts, during the pandemic, female analysts' likelihood of issuing a herding forecast increases by 2.68 percentage points, the likelihood of reissuing her previous forecast increases by 4.01 percentage points, the likelihood of issuing a rounded forecast increases by 1.30 percentage points, and the likelihood to issue a timely earnings forecast reduced by 3.03 percentage points. These changes represent 7.44% (2.68%/36.0%), 8.53% (4.01%/47.0%), 7.56% (1.30%/17.2%),

and 6.17% (3.03%/49.1%) relative to the unconditional means of female analysts before the pandemic, respectively.

3.2.5 Forecast optimism

One alternative explanation for the forecast accuracy result is that female analysts became more pessimistic when facing large adverse shocks. One possible reason is that women had more woman friends, and women were more negatively affected by the pandemic. Due to the experience effect (Malmendier and Nagel, 2011; D'Acunto, Malmendier, and Weber, 2020), such asymmetric exposure might lead women to have more pessimistic expectations about future economic prospects than men. If female analysts were overly pessimistic, such a gender difference in pessimism might explain why female analysts' forecasts became less accurate during the pandemic.

Our results rule out this alternative explanation. We measure analysts' forecast optimism directly. Specifically, we construct a measure of *Forecast Optimism*, defined as forecasted EPS minus actual EPS scaled by the 12-month lagged stock price and multiply by 100. A lower value of *Forecast Optimism* indicates more pessimistic earnings forecasts. This alternative explanation predicts that female analysts would make more pessimistic forecasts than male analysts. We replace *Forecast Error* with *Forecast Optimism* in an otherwise identical regression model as in our baseline analysis and report the results in Table 8. The results show that the coefficient of $Female * Post$ is positive, although statistically insignificant. The positive coefficient indicates that female analysts became more optimistic than male analysts during the pandemic, the opposite to the prediction of the alternative explanation. We also find a positive and significant coefficient

on *Forecast Age*, consistent with analysts' tendency to "walk down" their estimates to a level that firms can beat at the official earnings announcement (Richardson, Teoh, and Wysocki, 2004).

3.2.6 A placebo test based on the 2007-2009 global financial crisis

Besides becoming more pessimistic, female analysts' forecast accuracy may decrease more than males for other reasons. For example, studies show that men have a stronger preference for and a better ability to respond to the increased competitiveness (Gneezy, Niederle, and Rustichini, 2003; Niederle and Vesterlund, 2007; Reuben, Sapienza, and Zingales, 2015). If this applies to analysts, we should find a similar widening analyst gender gap during other economic crises. To examine this possibility, we use the 2007-2009 global financial crisis to conduct a placebo test. If female analysts tend to do poorer than male analysts during economic downturns, we expect female analysts' forecast errors increased more than male analysts during the 2007-2009 crisis. Suppose the increasing household responsibility was driving the reduced forecast accuracy of female analysts in 2020. In that case, we do not expect female and male analysts to be affected asymmetrically in the 2007-2009 crisis because it was not a shock to household responsibility.

Table 9 reports the results. Our analysis focuses on the period from January 2007 to March 2009. We define the post-period as the period from October 2007 to March 2009, a 17-month bear market during the global financial crisis. We infer analysts' gender based on their first names extracted from earnings conference call transcripts. This I/B/E/S sample has 2,032 unique analysts, and we can identify the full names of 1,541 analysts. Among 1,463 analysts whose gender can be unambiguously inferred from the first names, 1321 are male, and 142 are female.

The results reported in Table 9 show that the 2007-2009 global financial crisis did not increase female analysts' forecast error more than male analysts. If anything, during the 2007-2009 global financial crisis, female analysts' forecast error reduced more than male analysts', as indicated by the negative coefficient of $Female * Post$. However, the coefficient is statistically insignificant in all the specifications.

3.3 The market reaction

Finally, we examine whether investors are aware of the less accurate forecasts issued by female analysts during the pandemic. We estimate the following regressions:

$$CAR_{i,j,q,t} = \beta_1 + \beta_2 Female_i * Post_t + \beta_3 Frev_{i,j,q,t} + \beta_4 Frev_{i,j,q,t} * Female_i * Post_t + \beta_5 Frev_{i,j,q,t} * Female_i + \beta_6 Frev_{i,j,q,t} * Post_t + \gamma_{j,q} + \delta_{i,j} + \theta_t + \epsilon_{i,j,q,t}$$

The dependent variable $CAR_{i,j,q,t}$ is the three-day cumulative abnormal return for firm *j* centered on the forecast revision of quarter *q*'s EPS issued by analyst *i* at time *t*. Abnormal return is defined as raw return minus the return of the value-weighted CRSP market index. The variable $Frev_{i,j,q,t}$ is forecast revision, defined as the difference between the current quarterly earnings forecast of analyst *i* for firm *j* at time *t* and the earnings forecast for the same firm-quarter issued immediately before the current forecast, scaled by the 12-month lagged stock price. To calculate forecast revision, we require that an analyst issued both a current and prior earnings forecast for the same firm-quarter. We calculate forecast revision relative to an analyst's previous forecast instead of relative to the market consensus because changes relative to one's previous forecast are more informative (Stickel, 1991; Gleason and Lee, 2003). We also add *Forecast Age* and its interaction with forecast revision, *Frev**Forecast Age*, as additional controls in column (3). The coefficient of

*Frev***Forecast Age* is positive, suggesting that forecasts issued earlier in a quarter likely convey more novel information to investors, despite being less accurate on average.

Table 10 reports the regression results. As expected, the coefficient of $Frev_{i,j,q,t}$ is positive and highly significant, indicating that analyst forecast revisions contain information and the market reacts to them. The coefficient of $Frev_{i,j,q,t} * Female_i$ is significantly positive, suggesting that, before the pandemic, female analysts' forecast revisions were more impactful than male analysts' forecast revisions, consistent with Kumar (2010).

More importantly, we find that the coefficient on $Frev_{i,j,q,t} * Female_i * Post_t$ is negative and statistically significant. The magnitude of the coefficient is similar in all the specifications. The negative coefficient of $Frev_{i,j,q,t} * Female_i * Post_t$ more than fully offset the positive coefficient of $Frev_{i,j,q,t} * Female_i$. For example, in column (3), the coefficient of $Frev_{i,j,q,t} * Female_i * Post_t$ is -0.992 (t =-3.26) and the coefficient $Frev_{i,j,q,t} * Female_i$ is 0.699 (t = 3.90). A Wald test of the null that the sum of the two coefficients equals zero yields a p-value of 0.23. These results show that, during the pandemic, the market reacted less strongly to female analysts' forecast revisions than male analysts' forecast revisions, reversing the pre-pandemic pattern (although the difference is statistically insignificant).

Overall, the results show that the market was aware of the asymmetric impact of the pandemic to female and male analysts and down-weighted the forecasts issued by female analysts.

4. Conclusions

In this paper, we study the effects of the COVID-19 pandemic on female and male security analysts. Our difference-in-differences approach compares female and male analysts performing the same tasks: forecasting the same firms' earnings of the same fiscal quarter. We find that, relative to male analysts, female analysts' earnings forecast accuracy fell more during the early stage of the pandemic. We conjecture that this was driven by a relative increase in childcare and other household duties of women relative to men. We find that the effect was stronger when schools were closed, among the analysts who were more likely to have young children, and among analysts who were busier, inexperienced, and live in southern states. Relative to male analysts, during the pandemic, female analysts herded more closely with the consensus forecast, had a higher likelihood of reissuing their previous outstanding forecast, and had a higher likelihood of issuing a rounded forecast. Compared to male analysts, female analysts were also less likely to issue timely forecasts immediately following earnings announcements. This widening gender gap, however, decayed quickly and became statistically insignificant by May/June 2020.

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Figure 1. Dynamic effects of forecast accuracy

This figure plots the gender difference (the point estimates and their 95% confidence intervals) in forecast error by seven subperiods using the model in column 2 of Table 3. The seven subperiods are each of the five months around March 2020, December 2019 or before, and June 2020 or after. *Forecast Error* is 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. We estimate the gender differences relative to that of February 2020 in a full model with firm*fiscal quarter, year-month, and analyst*firm fixed effects and *Forecast Age* control. The confidence intervals are based on standard errors clustered at the analyst level.

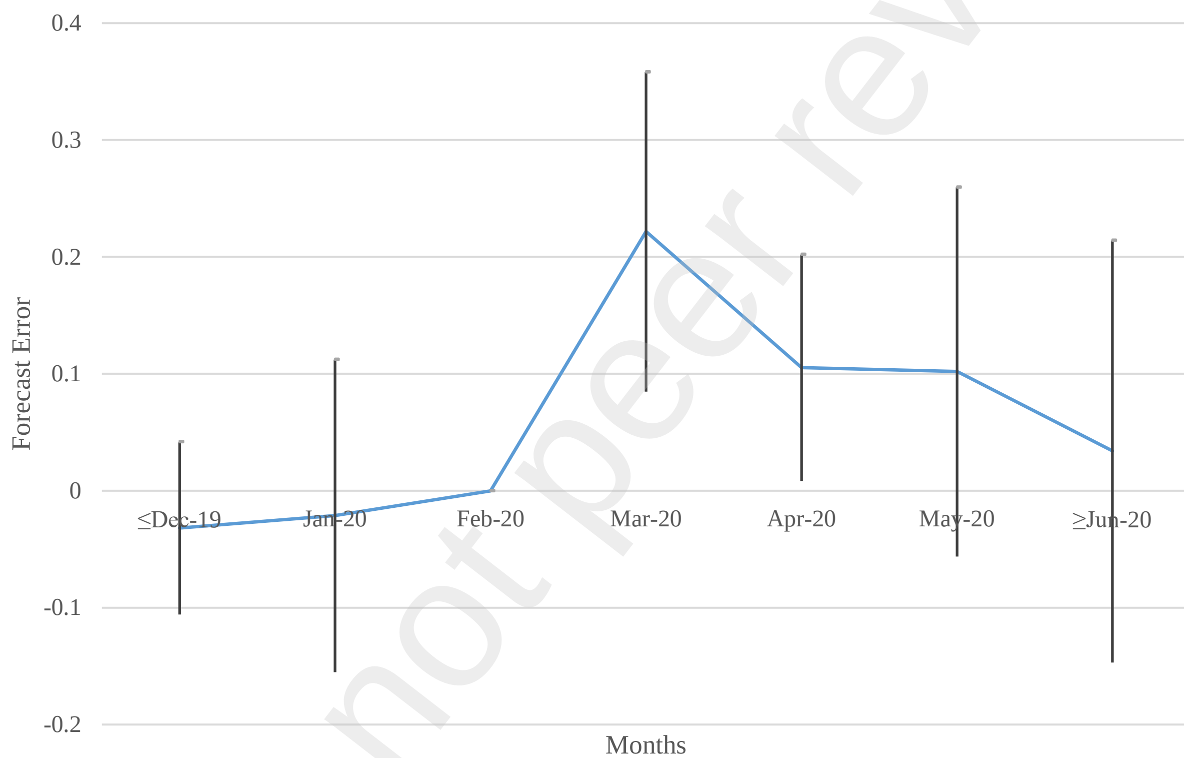

Table 1. Summary statistics

This table reports the summary statistics of the analysts by gender. Panel A reports the number of analysts, the number of brokerage firms affiliated with these analysts, and the analysts' age distribution. Panel B reports the summary statistics on analysts' forecast activities. We calculate the statistics in Panel B using the pre-pandemic data from January 2019 to February 2020. *Forecast Error* is 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Firms Covered* is the number of unique firms that the analyst issued at least one forecast over the sample period. *Updating Frequency* is the number of forecasts an analyst issues for every firm they cover at the monthly level. *Herding* is a dummy variable that takes the value of one for forecasts that are between the analyst's prior forecast and the consensus forecast, and zero otherwise. *Reissue* is a dummy variable that takes the value of one if a forecast is reissued, and zero otherwise. *Rounding* is a dummy variable that takes the value of one if a forecast ends with zero or five in the penny digit, and zero otherwise. *Timeliness* is a dummy variable that takes the value of one if an analyst issues an EPS forecast within days [0, +2] of a firm's quarterly earnings announcement, and zero otherwise. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date.

Panel A: Analyst brokerage and age distribution

	# of analysts	# of brokerage	Age in 2019		
			Mean	p10	p90
Male	1,744	177	37	22	52
Female	224	74	34	22	48
Full sample	1,968	184	37	22	52

Panel B: Forecast activities

	Female Analysts			
Variables	No. obs	Mean	Stdev	Median
Forecast Error	41,409	1.118	3.209	0.258
Firms Covered	218	12.197	8.275	11.000
Updating Frequency	36,827	1.124	0.353	1.000
Herding	10,537	0.361	0.480	0.000
Reissue	41,409	0.470	0.499	0.000
Rounding	41,409	0.172	0.377	0.000
Timeliness	41,409	0.491	0.500	0.000
Forecast Age	41,409	4.942	0.833	5.187

	Male Analysts			
Variables	No. obs	Mean	Stdev	Median
Forecast Error	343,428	1.145	3.383	0.254
Firms Covered	1,716	12.871	8.419	13.000
Updating Frequency	307,659	1.116	0.340	1.000
Herding	84,675	0.340	0.474	0.000
Reissue	343,428	0.511	0.500	1.000
Rounding	343,428	0.189	0.391	0.000
Timeliness	343,428	0.502	0.500	1.000
Forecast Age	343,428	4.957	0.825	5.193

Table 2. Baseline regressions on forecast error

This table reports the results on how COVID-19 affected the female and male analysts differently. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *Forecast Error*		
	(1)	(2)	(3)
*Female*Post*	0.1579***	0.1559***	0.1591***
	(3.17)	(2.93)	(3.00)
Post	-0.3961***		
	(-8.00)		
Forecast Age			0.2865***
			(14.06)
Adj.R-sq	0.723	0.721	0.724
N.of Obs.	448,978	448,034	448,034
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Table 3. Dynamic effects of forecast accuracy

This table presents the dynamic effects on how COVID-19 affected the female and male analysts differently. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. (December 2019 or before), (January 2020), …, and (June 2020 or after) are seven subperiod dummy variables. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *Forecast Error*	
	(1)	(2)
*Female**(*December 2019 or before*)	-0.0155	-0.0319
	(-1.31)	(-0.85)
*Female**(*January 2020*)	-0.0320	-0.0211
	(-0.51)	(-0.31)
*Female**(*February 2020*)	-0.0816*	
	(-1.79)	
*Female**(*March 2020*)	0.2309***	0.2218***
	(3.37)	(3.19)
*Female**(*April 2020*)	0.1271***	0.1054**
	(3.22)	(2.14)
*Female**(*May 2020*)	0.1251*	0.1021
	(1.84)	(1.27)
*Female**(*June 2020 or after*)	0.0467	0.0340
	(0.62)	(0.37)
Forecast Age	0.2809***	0.2864***
	(13.90)	(14.06)
Adj.R-sq	0.726	0.724
N.of Obs.	448,990	448,034
Firm*Fiscal quarter FE	Yes	Yes
Year-month FE	Yes	Yes
Analyst*Firm FE	No	Yes

Table 4. Updating frequency and firms covered

This table reports how COVID-19 affected analysts' updating frequency (Panel A) and the number of firms covered (Panel B). In Panel A, the dependent variable is *Updating Frequency*. We measure updating frequency at the analyst-firm-month level. Specifically, updating frequency is defined as the number of forecasts issued by analyst *i* in month *t* for firm *j*. In Panel B, the dependent variable is either *Firms Covered* or the natural logarithm of *Firms Covered*. The analysis is at the analyst-period level. *Firms Covered* is the number of unique firms that an analyst issued at least one forecast over the pre- or post-period. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Updating Frequency

	Dep.Var = *Updating Frequency*	
	(1)	(2)
*Female*Post*	0.0028	0.0035
	(0.33)	(0.39)
Post	0.0660***	
	(16.08)	
Adj.R-sq	0.119	0.160
N.of Obs.	398,787	397,801
Firm*fiscal quarter FE	Yes	Yes
Year-month FE	No	Yes
Analyst*Firm FE	No	Yes
Analyst FE	Yes	No

Panel B. Firms Covered

	Dep.Var = log(*Firms Covered*)		Dep.Var = *Firms Covered*	
	(1)	(2)	(3)	(4)
*Female*Post*	0.0878	0.0115	0.4517	-0.0033
	(0.85)	(0.42)	(0.54)	(-0.01)
Post	-0.0665**	-0.1478***	-1.0500***	-1.7160***
	(-1.97)	(-13.80)	(-3.70)	(-18.68)
Female	-0.0936		-0.6740	
	(-1.28)		(-1.13)	
Constant	2.2247***		12.8712***	
	(96.28)		(63.32)	
Adj.R-sq	0.001	0.905	0.003	0.907
N.of Obs.	3,537	3,138	3,537	3,138
Analyst FE	No	Yes	No	Yes

Table 5. The school closure effect

This table reports the results on the school closure effect. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Closure* is a dummy variable that takes the value of one if a forecast was issued when schools were closed in the state the analyst resided, and zero otherwise. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *Forecast Error*		
	(1)	(2)	(3)
*Female*Post*(Closure=0)*	0.1151**	0.0999*	0.1153**
	(2.24)	(1.84)	(2.13)
*Female*Post*(Closure=1)*	0.2175**	0.2733**	0.2457**
	(2.14)	(2.58)	(2.33)
Post(Closure=0)*	-0.3933***		
	(-6.84)		
Post(Closure=1)*	-0.2320***		
	(-4.88)		
Forecast Age			0.2778***
			(12.94)
Adj.R-sq	0.726	0.723	0.726
N.of Obs.	353,493	352,840	352,840
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Table 6. Cross-analyst heterogeneity

This table reports cross-analyst heterogeneity tests on forecast accuracy. In Panel A, we split our sample into four groups based on analyst's ages: less than 30, between 30 and 40, between 40 and 50, and older than 50. In panel B, we split our sample into three groups based on the number of firms covered by an analyst, analyst total experience, and analyst location. *Firms Covered* is the number of firms covered by the analyst in a year. *Total Experience* is the number of years since the analyst issued the first forecast for any firm. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Subsample test based on analyst age

	Dep.Var = *Forecast Error*			
	Age<=30	30<Age<=40	40<Age<=50	Age>50
*Female*Post*	0.1438	0.2812***	0.1383*	0.1476
	(0.51)	(4.60)	(1.74)	(1.21)
Forecast Age	0.3390***	0.2741***	0.2787***	0.3159***
	(5.58)	(14.13)	(12.12)	(12.09)
Adj.R-sq	0.718	0.745	0.718	0.698
N.of Obs.	17,472	145,396	171,336	108,788
Firm*Fiscal quarter FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Analyst*Firm FE	Yes	Yes	Yes	Yes

Panel B: Subsample test based on firms covered, total experience, and location of analysts

	Dep. Var = *Forecast Error*					
	Firms covered		**Total experience**		**Location**	
	<=median	>median	<=median	>median	Southern States	Other States
*Female*Post*	0.0593	0.3189***	0.2162**	0.0977*	0.3228**	0.1298**
	(0.82)	(4.32)	(2.53)	(1.72)	(2.47)	(2.14)
Forecast Age	0.2657***	0.3091***	0.2938***	0.2806***	0.3757***	0.2719***
	(11.82)	(14.16)	(12.85)	(13.58)	(7.19)	(15.90)
Firm*Fiscal quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst*Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-sq	0.740	0.707	0.712	0.737	0.722	0.722
N.of Obs.	210,175	233,166	218,713	224,917	66,424	381,246

Table 7. Forecast heuristics and timeliness

This table reports the results on analyst forecast heuristics and timeliness. We use three measures of forecast heuristics. The dependent variables are *Herding* in Panel A, *Reissue* in Panel B, *Rounding* in Panel C, and *Timeliness* in Panel D, respectively. *Herding* is a dummy variable that takes the value of one for forecasts that are between the analyst's own prior forecast and the consensus forecast, and zero otherwise. *Reissue* is a dummy variable that takes the value of one if a forecast is reissued, and zero otherwise. *Rounding* is a dummy variable that takes the value of one if a forecast ends with zero or five in the penny digit, and zero otherwise. *Timeliness* is a dummy variable that takes the value of one if an analyst issues an EPS forecast within days [0, +2] of a firm's quarterly earnings announcement, and zero otherwise. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Herding

	Dep.Var = *Herding*		
	(1)	(2)	(3)
*Female*Post*	0.0201**	0.0268**	0.0268**
	(1.98)	(2.35)	(2.35)
Post	-0.1455***		
	(-25.50)		
Forecast Age			0.0001
			(0.03)
Adj. R-sq	0.064	0.066	0.066
N. of Obs.	132,531	130,468	130,468
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Panel B. Rounding

	Dep.Var = *Rounding*		
	(1)	(2)	(3)
*Female*Post*	0.0106**	0.0130**	0.0130**
	(1.98)	(2.36)	(2.37)
Post	-0.0013		
	(-0.53)		
Forecast Age			-0.0044***
			(-4.36)
Adj. R-sq	0.076	0.071	0.071
N. of Obs.	448,978	448,034	448,034
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Panel C. Reissuance

Dep.Var = *Reissue*			
	(1)	(2)	(3)
*Female*Post*	0.0397***	0.0408***	0.0401***
	(4.82)	(4.82)	(3.24)
Post	0.0964***		
	(24.38)		
Forecast Age			-0.0682***
			(-8.98)
Adj.R-sq	0.128	0.189	0.196
N.of Obs.	448,978	448,034	448,034
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Panel D. Timeliness

Dep.Var = *Timeliness*		
	(1)	(2)
*Female*Post*	-0.0297***	-0.0303***
	(-4.10)	(-3.99)
Post	-0.1992***	
	(-46.73)	
Adj.R-sq	0.239	0.375
N.of Obs.	448,978	448,034
Firm*Fiscal quarter FE	Yes	Yes
Year-month FE	No	Yes
Analyst*Firm FE	No	Yes
Analyst FE	Yes	No

Table 8. Forecast optimism

This table reports the results on how COVID-19 affected analysts' forecast optimism. The dependent variable is *Forecast Optimism*, defined as 100 times the difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *Forecast Optimism*		
	(1)	(2)	(3)
*Female*Post*	0.0810	0.0817	0.0835
	(1.32)	(1.25)	(1.27)
Post	-0.9307***		
	(-18.59)		
Forecast Age			0.1646***
			(9.69)
Adj.R-sq	0.469	0.474	0.476
N. of Obs.	448,978	448,034	448,034
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Table 9. Placebo test based on the 2007-2009 global financial crisis

This table reports whether the 2007-2009 global financial crisis affected the female and male analysts differently. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from October 2007 to March 2009, a 17-month bear market during the global financial crisis. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. The overall sample period is from Jan 2007 to March 2009 in this test. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *Forecast Error*		
	(1)	(2)	(3)
*Female*Post*	-0.1292	-0.1813	-0.1873
	(-1.15)	(-1.44)	(-1.48)
Post	1.0477***		
	(10.39)		
Forecast Age			1.2445***
			(12.49)
Adj.R-sq	0.775	0.775	0.777
N.of Obs.	754,985	754,429	753,235
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Table 10. Stock market reaction to analyst forecast revisions

This table reports the results on the stock market reaction to analyst forecast revisions. The dependent variable is *CAR*(-1, +1), which is the three-day cumulative abnormal return for firm *j* centered on the forecast revision of quarter *q*'s EPS issued by analyst *i* at time *t*, where the abnormal return is defined as raw stock return minus the return of the value-weighted CRSP market index. *Frev* is forecast revision, defined as the difference between the current quarterly earnings forecast for analyst *i* following firm *j* at time *t* and the earnings forecast for the same firm-quarter issued immediately before the current forecast, scaled by the 12-month lagged stock prices. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dep.Var = *CAR*(-1,+1)		
	(1)	(2)	(3)
*Female*Post*	0.0017	0.0025	0.0025
	(0.75)	(1.02)	(1.02)
Frev	0.7629***	0.8029***	0.2319
	(6.04)	(6.46)	(0.74)
Frev*Female*Post	-0.9186***	-0.9959***	-0.9923***
	(-3.01)	(-3.37)	(-3.26)
*Frev*Female*	0.6667***	0.7170***	0.6990***
	(4.89)	(4.00)	(3.90)
*Frev*Post*	-0.6109***	-0.6537***	-0.6089***
	(-3.67)	(-4.08)	(-4.00)
Post	0.0030		
	(0.67)		
Forecast Age			0.0003
			(0.32)
*Frev*Forecast Age*			0.1383*
			(1.76)
Adj.R-sq	0.101	0.072	0.072
N.of Obs.	104,425	103,481	103,481
Firm*Fiscal quarter FE	Yes	Yes	Yes
Year-month FE	No	Yes	Yes
Analyst*Firm FE	No	Yes	Yes
Analyst FE	Yes	No	No

Internet Appendix

Table A1. Robustness tests

This table reports several robustness tests to the baseline results in the paper. In column (1), we report the results when we double-cluster standard errors by analysts and forecast months. In column (2), we winsorize *Forecast Error* at the 2% and 98% levels. In column (3), we focus on the period from September 2019 to August 2020 such that the pre- and the post-periods have the same length. In column (4), we use March 2019 to August 2019 as the pre-period to control for the possible seasonality effect in analyst forecasts. In column (5), we control for a group of analyst characteristics. The dependent variable is *Forecast Error*, defined as 100 times the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. *Female* is a dummy variable that takes the value of one for female analysts, and zero for male analysts. *Post* is a dummy variable that takes the value of one for forecasts issued from March 2020 to August 2020. *Forecast Age* is the natural logarithm of the number of days from the forecast to the earnings announcement date. *Log*(*Firms Covered*) is the natural log of the number of firms that an analyst covers in a year. *Broker Size* is the natural log of the total number of analysts working for a brokerage firm in a year. *Total Experience* is the number of years since the analyst first issued an earnings forecast for any firm. *Firm-specific Experience* is the number of years since the analyst first covered the firm minus the average number of years for all other analysts covering the same firm. Analyst characteristics are calculated using data up to the month before forecast accuracy. Standard errors are clustered at the analyst level, and *t*-statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Standard error clustered at analyst and month level	Forecast accuracy winsorized at 2% and 98%	sample period from 2019/09 to 2020/08	use March 2019 to August 2019 as the pre-period	control for analyst characteristics
*Female*Post*	0.1591**	0.1473***	0.1125**	0.1697***	0.1841***
	(2.76)	(3.48)	(2.16)	(2.63)	(3.03)
Forecast Age	0.2865***	0.2440***	0.3386***	0.2724***	0.2918***
	(7.06)	(20.35)	(8.74)	(13.18)	(13.75)
Log(Firms Covered)					-0.0572*
					(-1.81)
Broker Size					-0.0056
					(-0.21)
Total Experience					0.2021
					(1.09)
Firm-specific Experience					-0.0923
					(-1.04)
Adj.R-sq	0.724	0.703	0.681	0.710	0.723
N.of Obs.	448,034	448,034	182,921	248,858	392,924
Firm*Fiscal quarter FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Analyst*Firm FE	Yes	Yes	Yes	Yes	Yes